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Are small investors naïve?*

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Abstract

Traditional economic analysis of markets with asymmetric information assumes that the uninformed agents account for incentives of the informed agents to distort information. We analyze whether investors in the stock market are able to account for such incentive distortions. Security analysts provide investors with information about investment opportunities by issuing buy and sell recommendations. The recommendations are likely to be biased upwards, in particular if an analyst is affiliated with an investment bank that is a recent underwriter of the recommended firm. Using the trading data from the New York Stock Exchange Trades and Quotations database (TAQ), we find that small (individual) investors do not account for these distortions. While large (institutional) investors generate abnormal volumes of buyer-initiated trades only after positive recommendations of unaffiliated analysts, small traders also exert abnormal buy pressure after positive recommendations of affiliated analysts. Since stocks recommended by affiliated analysts perform significantly worse than those recommended by unaffiliated analysts, small traders suffer losses due to their naiveté. Increased competition among analysts does not remedy the informational distortion and adverse welfare effects.

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I. Introduction

Traditional economic analysis of markets with asymmetric information builds on the assumption that uninformed agents account for the incentives of informed agents to distort information. In the lemons model (Akerlof 1970), the uninformed agent understands that the informed agent does not have an incentive to reveal negative features of the commodity and that he would rather advertise the lemon as a "hidden gem." Consequently, the uninformed agent does not listen to such unverifiable information, and the informed agent abstains from providing it in the first place.

This result changes dramatically if the uninformed agent is naïve about the information provided. If uninformed agents were to take unverifiable information at face value, the informed agents would want to provide biased information and would make profits from subsequent economic interaction.

What happens in real markets? Are agents sophisticated enough to understand the informed agents' incentives to bias information? Or do they naively trust the informed agents and follow their advice too often?

In this paper, we analyze naïveté about distorted information in the market for stocks and stock recommendations. Analysts of brokerage firms are more informed about the value of a stock and provide investors with information in the form of buy/hold/sell recommendations. They have, however, incentives to distort this information, especially if their brokerage firm belongs to an investment bank whose corporate finance department is underwriting security issuances of firms covered by the analysts. Positive analyst coverage after an equity issuance is often viewed as part of an implicit agreement between underwriter and issuer.[1] Moreover, analysts have financial incentives to cover those stocks favorably since their compensation depends on their "support" in generating profits for the corporate finance department.[2]

If investors were rational, they should discount for such informational distortions of analyst recommendations. In particular, they should react less to recommendations from analysts who are affiliated with the underwriter of an issuer than to the recommendations of unaffiliated analysts. In turn, brokerage firms would specialize in recommendations about firms with which they are not in an underwriting relationship. If, however, investors are naïve and do not discount

[1] Michaely and Womack (1999).

[2] *The Economist*, "The price of atonement," Nov. 16, 2002; *New York Times*, "Wall Street's Harsh New Reality," Aug. 17, 2003.

enough for analysts' incentives, those investors might overreact to positively distorted recommendations. In this case, having analysts and corporate finance divisions united under one roof becomes a profitable business.

In this paper, we examine empirically whether investors account for analysts' incentives in their trading decision. As in previous behavioral literature on the role of biases in markets, we suggest that individual agents may be subject to biases, while firms – due to specialization, experience, and competitive pressure – display fully rational behavior.[3] Accordingly, we will distinguish between small (individual) and large (institutional) investors, based on the trade size. Using trading data from the New York Stock Exchange Trades and Quotations (TAQ) database (1993-2002), we find distinctly different trade reactions to recommendations among large and among small investors. Large investors react positively to buy and strong-buy recommendations of unaffiliated analysts, but do not display any abnormal trading behavior after positive recommendations issued by affiliated analysts. Small traders also react positively to buy and strong-buy recommendations of unaffiliated analysts – but they are equally, if not more, enthusiastic about stocks recommended by affiliated analysts.

We show that such trading behavior hurts small investors. Following the recommendations of affiliated analysts generates significantly lower returns than following unaffiliated analysts' advice. Over any investment horizon between 3 months and 5 years, the unaffiliated portfolio outperforms the affiliated portfolio.

We perform additional empirical tests to better understand the cause of the sub-optimal behavior of small investors. In particular, it is conceivable that small agents react equally to recommendations of affiliated and unaffiliated analysts not because they are naïve, but simply because it is too costly for them to find out which analyst is affiliated with respect to a specific stock. Three empirical results suggest that the rational explanation does not apply.

First, if small investors were just lacking information about analyst affiliation, their average reaction to recommendations should be weaker than, or at most equal to, that of large investors. We find, however, that small investors react relatively more strongly to recommendations compared to large investors.

Second, small investors would benefit from focusing on analysts who are "obviously" unaffiliated, for instance because their brokerage does not have any associated corporate finance

[3] DellaVigna and Malmendier (2003); Fisman (2003).

department. Such information is easy to collect and, in fact, advertised by unaffiliated brokerage firms. However, the trade reaction of small investors implies that they do not pay special attention to analysts who are "never affiliated."

Third, the only event that triggered a reduction in small investors' response to affiliated analysts during our sample period appears to be the analyst scandals of 2001 and 2002. After the intense media coverage of distorted recommendations and the various lawsuits, small investors appear to react less strongly to affiliated analysts. The change in behavior suggests that only when seeing evidence of the distortions did small investors realize the consequences of incentive conflicts; knowledge of the incentive conflict alone was not enough.

We thus interpret our results as evidence that small investors are naïve about incentive conflicts on the part of analysts and fail to discount their advice sufficiently. Their biased decision-making, based on distorted advice, has negative welfare consequences, as demonstrated by the negative portfolio returns of affiliated recommendations.

Further empirical analysis indicates that the competitive forces of market interaction do not remedy the bias in individual decision-making. Quite to the contrary, we show that recommendations about stocks that are covered by more analysts are more likely to be distorted upwards, not less.

The findings of this paper relate to other market settings in which the more informed agent gives advice to the less informed agent even though the two agents have conflicting interests. For example, firms provide consumers with product information in advertisements, but will not present any negative features. Consumers who take all advertisements at face value are likely to over-consume or to misallocate their resources. Similarly, salesmen can judge which product is most suitable for their clients, but will also be inclined to recommend the most expensive product in order to maximize their commission. Or, consider a doctor-patient relationship. The doctor is able to recommend appropriate treatments, but he may also be tempted to propose unneeded procedures in order to increase his revenues.

Our findings suggest that individuals do not always account for the misalignment in incentives, but follow distorted advice too much. A competitive market setting appears to be insufficient to endogenously trigger the rise of institutions that are committed to the interest of the individual consumer.

This paper relates to two main branches of literature in behavioral economics and finance. In behavioral economics, the questions of whether biases in individual decision-making persist in market settings, and how biases may affect the industrial organization in these markets is of increasing interest. A number of papers show that market interaction does not eliminate biases but may rather exacerbate their effect since firms tailor their contracts and products to take advantage them (DellaVigna and Malmendier, 2003; Gabaix and Laibson, 2003). The specific bias, naiveté about distorted advice, may be related to the experimental finding that subjects embrace the advice of other subjects, even if the advice-givers do not have superior information (Schotter, 2003).

In the finance literature, this paper builds upon the evidence in Lin and McNichols (1998) and Michaely and Womack (1999) that stock recommendations by affiliated analysts are more favorable but perform more poorly over short (3-day) and long (up to 2-year) horizons. Iskoz (2002) confirms these results for strong buy recommendations and provides evidence that institutional investors may be accounting for the distortions of affiliated analysts, as far as one can deduce from the quarterly changes in institutional ownership. Finally, our paper relates to the market micro-structure literature on trading reactions. We employ the modified Lee and Ready (1991) algorithm to classify trades as buyer- or seller-initiated (following Odders-White 2000) and measure trade reaction as in Lee (1992) and Hvidkjaer (2001).

The remainder of the paper is organized as follows. Section 2 describes the research design and empirical strategy. Section 3 provides details on the various sources of data employed in this study. In Section 4, we present the empirical results on distortions in analyst recommendations, on the trade reaction of small and large investors, and on the associated returns. We also discuss alternative explanations for the trading behavior of small investors. Section 5 explores, in more details, how firms incorporate the biases in individual trade decisions, and points to the effects of competition among analysts (as proxied for by coverage). Section 6 concludes.

II. Empirical Strategy

II. 1 Analyst Incentives

Sell-side analysts issue recommendations about the specific set of stocks they are "covering." Recommendations typically range from "strong sell" to "strong buy." These recommendations are published in various forms such as analyst reports, references to these reports in online data sources,[4] radio and TV interviews on CNBC and other channels.

Sell-side analysts face a well-known conflict of interest when providing investment advice in the form of recommendations. On the one hand, it is their job to provide profound security analyses and reliable recommendations to customers. Customers will, in turn, invest in the recommended stocks via the associated brokerage firm. The brokerage firm earns trading commissions and additional fees for their recommendations and reports. Good recommendations enhance the reputation of an analyst and thus lead to higher compensation.[5]

On the other hand, analysts have incentives to bias their recommendations upwards. One reason is simply that buy recommendations are more likely to generate trading business than sell recommendations. A buy recommendation can induce any investor to buy a stock; a sell recommendation, however, is mostly relevant for current owners of the stocks, given the short-selling constraints investors face. Another reason for analysts to bias recommendations upwards is underwriting business. Favorable recommendations are generally viewed as a precondition for investment banks to get future underwriting deals and as an implicit condition of existing underwriting contracts. Analysts whose brokerage firm is associated with an investment bank are likely to be exposed to pressure (and monetary incentives) from corporate finance departments to support underwriting business with positive recommendations.

As a results, analysts are trading off their reputational capital with the incentive to generate portfolio transactions and, in the case of affiliation with an investment bank, the incentive to generate underwriting business.

II. 2 Investor Rationality

The effect of these incentive distortions on analyst behavior depends on investor rationality. If investors rationally accounted for the incentives of analysts, they would discount positive analyst recommendations in general and those of analysts affiliated with an underwriting investment bank in particular. I.e. their buy reaction in responses to positive recommendations should be weaker than their sell reaction in response to negative recommendations. And their buy reaction should be stronger in response to positive recommendations of unaffiliated analysts than to those of affiliated analysts. Moreover, given the negative effect of investment distortions on

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[4] Examples are *briefing.com*, *FirstCall* of Thomson Financial, and *finance.yahoo.com*.

[5] Hong and Kubik (2003); Hong et al. (2000).

analyst reputation, analysts might, in turn, not issue recommendations about companies for which their investment bank is underwriting security issuances.

If, however, investors are naïve about the effect of incentives, then issuing biased recommendations becomes a profitable business. Naïve agents do not account for the general upward bias and react too strongly to recommendations on average; and, naïve agents do not account for the additional incentive distortion of affiliated analysts and display the same reaction to affiliated and unaffiliated recommendations.

While we can test whether investors differentiate between affiliated and unaffiliated analysts, it is harder to assess empirically whether investors react "too much" to analysts recommendations on average. Here, we need a rational benchmark.

We suggest that the trading behavior of large (institutional) investors is such a benchmark, i.e. that large traders are able to account for the misaligned incentives of analysts, while small (individual) investors naively follow the advice of analysts. The distinction between large and small investors reflects that large, institutional investors, such as pension funds, benefit from numerous professional resources that allow them to overcome the biases of individuals. First, institutional investors have professional investment managers. These managers devote their entire attention to making investment decisions on behalf of their company. Moreover, they specialize in certain types of investments or particular industries. For individual investors, instead, the investment of personal funds is just one of various, widely different decisions that they have to make every day. Repetition, more frequent feedback, and specialization make it easier for decision-makers in large institutions to learn about analysts' incentives to distort information. Second, institutional investors are subject to market pressure. Institutions that invest sub-optimally – for instance, because they are not accounting for distortions in analyst information – lose investors and will be driven out of the market. No such pressure exists for individual investors. Third, sorting works in favor of institutional investors. Individuals who decide to work in the finance industry and are successful enough to find such a job in a large institution have a better financial education and better skills in financial decision-making than the average individual investor. This reasoning is supported by findings in the previous literature, such as the anomalous trade reaction of small traders to earnings news (Lee 1992).

Adopting the trading behavior of large investors as the rational benchmark, investor naiveté gives us four empirical predictions.

Prediction 1. Recommendations of affiliated analysts are more biased upwards than those of unaffiliated analysts.

Prediction 2. Large investors exert less buy pressure in response to buy recommendations of affiliated analysts than in response to those of unaffiliated analysts.

Prediction 3. Small investors do not less buy pressure in response to buy recommendations of affiliated and unaffiliated analysts.

Prediction 4. Small investors exert more buy pressure on average in response to buy recommendations than unaffiliated analysts.

II. Empirical measures

We separate small and large investors by trading size. Following the analysis of Lee and Radhakrishna (2000), we choose dollar cutoffs rather than share-based cutoffs in order to minimize noise in separating individuals from institutions. We also incorporate their suggestion to use two cutoffs, with a buffer zone between small and large trades. Specifically we choose the cutoffs based on results for three-month TORQ sample from 1990-91, in which actually information on the identity of traders was available to check the accuracy of the trade-size based classification method. The lower cutoff of $20,000 splits small and medium trades, and the higher cutoff of $50,000 splits medium and large trades.[6]

Our empirical measures of analyst affiliation are based on the underwriting relationship of the analyst's brokerage house with the firm the analyst is reporting on. As in the previous literature[7], we first identify analysts as affiliated if the corporate finance division of their investment bank was the lead underwriter of an IPO of the recommended firm in the past five years or of an SEO in the past two years. We also include co-underwriters over the same respective periods.

We further examine two additional possible sources of underwriting bias. First, we look at future underwriting, i.e. analysts firms that underwrite an SEO in the next one or two years. Future underwriting may be a source of bias since the investment bank may want to please the firm it is recommending in order to gain underwriting business. The number of additional firms we capture with this measure is small though, since most future underwriters are in previous underwriting relationships. Second, we analyze bond underwriting, in particular lead underwriting of bonds in the past year. If positive coverage is part of an implicit agreement

[6] The results are robust to variations in cutoff, such as $10,000 for the lower cutoff and $20,000 for the upper cutoff.

[7] Lin and McNichols (1998); Michaely and Womack (1999).

between underwriter and equity issuer, then there is no obvious reason why this should not be the case for bond issuance as well.

II. 3 Trade Reaction

To capture the reaction of small and large investors to analyst recommendations, we employ measures of "directional trade" or "trade imbalance." These measures, first developed by Lee and Ready (1991), aim at capturing the buy pressure exerted by traders. They exploit the fact that most trades take place when one side of the transaction demands immediate execution. The total trade volume is analyzed trade-by-trade and decomposed into "buyer-initiated" and "seller-initiated" trades, depending on which side demanded immediate execution. An abnormally high balance of buyer-initiated trades indicates buy pressure; an abnormally high balance of seller-initiated trades indicates sell pressure.

We use the modified version of the Lee and Ready (1991) algorithm, developed in Odders-White (2000), to determine which side initiated the trade. The algorithm matches a trade to the most recent quote, which precedes the trade by at least 5 seconds. If a price is nearer the bid price it is classified as seller initiated, and if it is closer to the ask price it is classified as buyer initiated. If a trade is at the midpoint of the bid-ask spread, it is classified based on a "tick test". If the trade occurs at a price higher than the price of the previous trade (uptick), it is classified as buyer initiated; if the trade is on a downtick, it is classified as seller initiated. We drop trades at the bid-ask midpoint, which are also the same price as the preceding trades.[8]

In order to aggregate across firms and to compare between different types of investors, we calculate abnormal trading measures. As a measure of buy pressure, we will consider both the net number buy-initiated trades

$$NB_{i,x,t} = buys_{i,x,t} - sells_{i,x,t}$$

for firm i, investor type x, and date t, and a measure of trade imbalance. The raw trade imbalance measure for firm i, investor type x, and date t is calculated as:

$$TI_{i,x,t} = \frac{buys_{i,x,t} - sells_{i,x,t}}{buys_{i,x,t} + sells_{i,x,t}} \tag{5}$$

[8] The original Lee-Ready algorithm employs a "zero-tick" in the case that a trade is at the bid-ask midpoint and the same price as the previous trade. Because of its low accuracy (about 60% according to Odders-White, 2000) the "zero-tick" is left out in the modified Lee-Ready algorithm.

Alternatively, we normalize this measure, and our raw buy and sell measures, by subtracting off the firm-year mean, and dividing by the firm-year standard deviation.

$$TI_{i,x,t}^{abnormal} = \frac{TI_{i,x,t} - \overline{TI}_{i,x,year(t)}}{SD(TI_{i,x,year(t)})} \qquad (6)$$

The adjustments are made by year because the average trading behavior changes significantly over time, and by firm because the trading behavior for various firms may have consistent differences. This allows us to aggregate across firms without concerns for differences in the non-event-time trading behavior associated with them. Normalizing the measures by the standard deviation allows us to make qualitative comparisons between small and large investors. Moreover, without the normalization, a seemingly more extreme reaction could be the result of higher volatility in trade imbalances over time. Dividing by the standard deviation controls for systematic differences in the volatility of large trades and small trades or in the volatility of the stocks large and small traders invest in.

III. Data

We analyze three main sources of data: data on securities trading, data on analyst recommendations, and data on underwriting.

The raw trading data is collected from the New York Stock Exchange Trades and Quotations database (TAQ). The TAQ database reports every round-lot trade and every quote from January 1, 1993 onwards on the New York Stock Exchange, American Stock Exchange and Nasdaq. We examine ordinary common shares traded on the NYSE, excluding certificates and depository receipts. We also exclude foreign companies, Americus trust components, closed-end fund shares and REITs. The final trading sample includes 2801 securities for 2723 firms, as defined by 8-digit and 6-digit CUSIPs, respectively.

We obtain analyst recommendations and information about the analyst and brokerage firm from I/B/E/S starting from October 29, 1993. I/B/E/S converts the recommendation formats of different brokerage houses into one uniform format (from 1 for “strong buy” to 5 for “strong sell”). Like other authors (Jagadeesh, Kim, Krische and Lee, 2002), we reverse the original I/B/E/S coding to the following scheme: 5=strong buy, 4=buy, 3=hold, 2=sell, 1=strong sell to make the ordering more intuitive. A “higher” recommendation is better and an “upgrade” translates into a positive change in the numerical value.

We use the SDC New Issues database to obtain underwriting data 1987 to 2002. We link I/B/E/S broker firms and SDC underwriters with the company names provided by the I/B/E/S recommendation broker identification file and the SDC database. We improve the match using company websites and news articles, in particular to determine subsidiary relationships and corporate name changes. Finally, we used the mapping from Kolasinski and Kothari (2003) to identify additional matches.[9]

In addition, we use CRSP for security prices, returns, and share information, and COMPUSTAT for financial variables of the companies. The merged data set extends from October 29, 1993 through December 31, 2002 (with underwriting data from 1987 on), and contains 173,950 recommendations with linked trading data, for 2424 securities of 2397 firms. Notice that only 12% of the firms in our NYSE sample lack recommendations, so that our final sample contains almost the entire set of domestic NYSE firms with common stock.

There are an unusually high number of recommendations made during the first three months of the sample period, although this may be due to differences in the way I/B/E/S dealt with data at the beginning of the sample period. While the number of recommendations per year – and even per month – is fairly uniform during the period from February 1994 through 2001, the first two and a half months contain a multiple of observations. From February 1994 on, number gradually increases from 11596 in 1995 until in peaks at 13944 in 1999. The number of recommendations declines in 2000 and 2001, but then skyrockets in 2002, with a total of 20560 recommendations made that year. To exclude the "scandal effects" from 2001 and 2002 and reporting anomalies in the I/B/E/S data set, we replicated all regressions for the period from February 1994 through July 2001, containing 2252 securities and 2229 firms.

IV. Empirical Analysis

IV.1. Analyst Bias

We first analyze the distribution of recommendations (from "strong sell" to "strong buy") among affiliated and unaffiliated analysts. As Table I shows, analysts make very few strong sell and sell recommendations, regardless of their affiliation. If investors were to take the titles given to analyst recommendations literally, they would constantly be purchasing securities. The

[9] We are very grateful to Adam Kolasinski and S.P. Kothari for providing us with their mapping, which uses corporate websites, news articles from LexisNexis, Hoover's Online, and the Directory of Corporate Affiliations to refine the matches.

strikingly skewed distribution is consistent with analysts' incentive to issue buy recommendations rather than sell recommendations simply from the amount of trading business this will generate.

Table I also displays the distribution of recommendations for each type of underwriting affiliation with the recommended firms. "IPO lead underwriting" affiliation means that the analyst's investment bank was the lead underwriter of an IPO in the past 5 years. Similarly if the investment bank underwrote an SEO in the past 2 years, the analyst is "SEO lead underwriting" affiliated. "Co-underwriting" affiliation is defined for the same period.

We also analyze two types of underwriting affiliations that have not been explored in the previous literature. The first type of affiliation is due to future equity underwriting. An analyst whose firm is planning on underwriting an equity offering may be pressured to issue higher recommendations, in order to please the issuer and to receive a better price on the equity offering. Alternatively, the very reason the investment bank chooses to underwrite may be that they view the company very favorably, resulting in unconscious rather than conscious "distortion." Another potential source of conflict which has not been examined is bond underwriting.

Overall, there are a total of 11,017 affiliated recommendations, about 9.1% of the total recommendation sample, containing 121,130 recommendations. The summary statistics show that any type of affiliation leads to more positive recommendations than unaffiliated analysts. The affiliated analysts make even fewer strong sell and sell recommendations than unaffiliated analysts. Affiliated analysts also make far more buy and strong buy recommendations than the average analyst. Note, though, that the sample size is very small for future equity underwriting, since most "future" underwriters are already in current underwriting relationships.

We also separate out firms that do not underwrite securities at all. We proxy for this group by looking at the set of firms that do not underwrite an equity issuance or act as the lead underwriter for a bond issuance during our SDC sample period of 1987 through 2002. Non-underwriting firm analysts make the most strong sell and sell recommendations of any group we look at. The extremely low number of affiliated sell and strong sell recommendations becomes even more striking when we examine the timing of these recommendations. The few sell and strong sell recommendations that are made by affiliated analysts in our sample are almost exclusively from 2002. For example, 69 out of the 154 SEO or IPO lead and co-underwriter affiliated sell and strong sell recommendations come out in 2002. Twenty-two of those recommendations were made by analysts from Morgan-Stanley, as the firm worked on improving their analysts' reputations and minimizing the effect of the SEC investigation of their analysts' conflicts of interest. Similarly, a few other firms began issuing more and more pessimistic recommendations while affiliated during this later period, as investors became more aware of possible conflicts. For the entire sample period affiliated recommendations appear higher, but if we limit the sample to 1993-2001, the difference is even stronger.

We consider the possibility that positive recommendations made by affiliated analysts are caused by differences in the firms being covered. Stocks that have recently issued securities may be truly of higher quality, as evidenced by their ability to access the capital markets. We thus restrict our sample to recommendations on firms that have recently issued stock or bonds. Panel B of Table I shows that we obtain the same statistics. The higher recommendations are not due to characteristics of the firms that have issued new securities, but of the affiliated analysts themselves.

Further evidence that the differences do not arise from differences in the firms being covered is presented in Table II. A detailed look at the industries covered by each group shows that there are no significant differences.

The timing of the different types of recommendations helps to further pin down "distortions" in the recommendations of affiliated analysts. It would have been conceivable that part of the upward bias is due to quicker reactions of affiliated analysts. They may issue a "strong buy" as soon as they receive indications of future growth prospects, even if they have to revise it soon after. Results shown in Table III suggest that affiliated analysts do the opposite. They just stick to positive recommendations longer than unaffiliated analysts, and update negative recommendations more quickly. Affiliated analysts maintain strong sell and sell recommendations for just over half the time unaffiliated analysts maintain these negative recommendations. Affiliated analysts also update hold recommendations more quickly than unaffiliated analysts. But affiliated analysts do not update their buy and strong buy results as often, leading to issuing recommendations less frequently overall.

A related question is how the recommendations of affiliated analysts compare to the existing analyst consensus. Table IV compares the recommendations of the different analyst groups to the existing consensus recommendation, where the consensus is the average recommendations over the preceding month. (Alternative periods for the construction of the consensus yield similar results.)

It turns out that affiliated analysts do not deviate much from the current consensus. Instead, they issue their positive recommendations when the consensus is high – in fact higher than the consensus at which unaffiliated analysts issue the same recommendations. For example, analysts tend to issue buy recommendations when the consensus is below buy. But IPO lead-underwriting affiliated analysts, and IPO and SEO co-underwriting affiliated analysts, issue buy recommendations when the consensus is above buy.

This behavior makes it hard for investors to identify "blatant" distortions. If an analyst were to issue a strong buy recommendation when the consensus is low, the recommendation would stand out. Instead, the affiliated analysts appear to "wait" until the consensus is high enough to justify positive recommendations. As we saw earlier, the affiliated analysts then maintain these positive recommendations much longer than unaffiliated analysts.

Another observation we can make from Table IV is that affiliated analysts tend to issue strong sell, sell or hold recommendations when the consensus is lower than the consensus when unaffiliated analysts do the same. This suggests that, not surprisingly, affiliated analysts are only issuing such negative recommendations when the consensus is especially low.

Overall, there is evidence that analysts exhibit two types of bias. First, all analysts issue primarily hold, buy and strong buy recommendations. Second, analysts with underwriting affiliations tend to issue even more strongly positive recommendations. We found that affiliated analysts issue positive recommendations when other analysts are issuing positive recommendations as well, but then maintain these recommendations significantly longer than unaffiliated analysts. Similarly, affiliated analysts only issue negative recommendations when the situation is especially bad, but then upgrade in a much shorter time than unaffiliated analysts.

IV.2. Trade Reaction

The incentives faced by analysts seem to have an effect on their recommendations. Overall, analysts almost never recommend selling a stock. Underwriting-affiliated analysts issue even more positive recommendations than unaffiliated analysts, and consistently issue more buy and strong buy recommendations than unaffiliated analysts. The primary question of this section is the following: Do investors account for these distortions in their trading decisions? In order to answer this question, we look at buying and selling behavior of small and large traders

We apply different measure of trade imbalance to identify the buy or sell reaction triggered by recommendations. In particular, we use market microstructure algorithms to determine which side of that trade demanded more immediacy. In general, that side of a trade represents a market order. The idea is that an investor who has gotten very positive news about a firm and believes that the stock price would rise consistently from now on, he would not place a limit order to buy. (That limit order would never be filled.) Instead, he would place a market order, and demand to buy before the price went up.

Table V presents summary statistics for our trading measures, both for the overall sample period and for the days of recommendations. While small investors execute more trades per day, the average difference between buy- and sell-initiated trades are very similar, 3.18 for small trades and 3.43 for large trades, over the entire sample period. The median is 0 for both small and large trades.

To test the trader reactions to recommendations, we employ event-study methodology. Our primary event period is trading days 0 and 1 around the event, where day 0 is the first trading day on or after the recommendation. As we can see from the summary statistics for trading behavior during these days, the difference between buys and sell is considerably higher, both for small and large trades on the days of recommendations (9.65 for small trades and 9.97 for large trades), indicating systematic buy-pressure induced by the recommendations. We further employ a normalized measure of trade imbalance (as introduced in Section II), which allows more straightforward comparisons across firms and across investor groups.

We conduct our trading regressions with two different measures of trade behavior. Our first measure is the number of buy-initiated trades minus number of sell-initiated trades over the event period. Our second measure is the sum of the normalized trade imbalance over the same period. Note that longer horizons (up to 20 trading days after the recommendation) lead to similar results, indicating that small traders keep reacting to recommendations over some time period.

Regression (1) shows large investors initiate an average of (net) 20 additional trades as buyers, when an unaffiliated buy recommendation is issued, but they make only 7 additional purchases if the buy recommendation is from an affiliated analyst. Both the positive reaction to the unaffiliated recommendation and the difference between the reactions, to affiliated and unaffiliated analysts, are significant. Similarly, for strong buy recommendations large investors initiate 24 or 11 additional buys for unaffiliated and affiliated recommendations, respectively, with the difference being significant.

The behavior of small investors is rather different. They about the same amount for unaffiliated recommendations, about 20 additional net purchases for a buy and 24 for a strong buy recommendation; but they do not reduce their buy pressure if the buy or strong buy recommendation comes from an affiliated analyst. Instead, they generate about 28 net purchases for a buy recommendation and 29 for a strong buy recommendation.

The results using the normalized trade imbalance show a similar pattern. While large investors' imbalance is positive for unaffiliated buy and strong buy recommendations, it is slightly negative for the same affiliated recommendations, and the correction for affiliation is significant. Small traders have an even higher trade imbalance for the unaffiliated recommendations than large traders, and a significantly higher imbalance for affiliation.

These results indicate that large traders account for the incentives of affiliated analysts to issue more positive recommendations. Small traders do not make this correction.

The normalized trade imbalance results also suggest that small investors take analyst recommendations more literally than large traders. Regression (2) also shows that small investors react more strongly both to sell and to buy recommendations, as all interactions of "strong sell" and "sell" with "small trade" have a negative effect on the trade imbalance, and all interactions of "strong buy" and "buy" with "small trade" have a positive effect. This behavior indicates that small investors discount recommendations less on average, compared to large investors, and thus account less for potential distortions.

IV. 3. Returns

To understand whether small traders suffer negative welfare consequences from naively following affiliated analysts, we evaluate the returns from trading based on the analyst recommendations. We construct two different portfolios. In one, the recommendations of all affiliated analysts are followed – stock is purchased for a buy or strong buy recommendation, and sold for a sell or strong sell recommendation. In the second portfolio, the same is done, but following only unaffiliated analysts. We then examine both the buy-and-hold returns and the cumulative abnormal returns of these portfolios over many different time horizons.

We estimate abnormal returns using the market model. We form event-time portfolios based on recommendations and estimate the relation of event-time portfolio and market portfolio over the one-year period ending two months before the event as follows:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it}$$

where $R_{i,t}$ is the return on portfolio i on day t,

$R_{m,t}$ is the return on the market portfolio on day t.

We then use the estimated values of α and β to calculate the abnormal return during and after the event period. The abnormal return is the difference between the realized portfolio return and the predicted return based on the estimated parameters and the realized market returns.

$$AR_{it} = R_{it} - \left(\hat{\alpha} + \hat{\beta} R_{mt}\right)$$

We evaluate buy-and-hold returns over a number of horizons. Since the analyst issuing a recommendation is likely to be evaluated during the same year, the performance over the next six months to one year might be most relevant. On the other hand, small investors may not re-evaluate the position for years to come. Thus, also longer horizons are of interest from the perspective of the investors.

Regardless of the particular time horizon, we find that following affiliated recommendations leads to lower (more negative) returns than following unaffiliated analysts. Table VI presents the specific return results over 3 months, 6 months, the first, second and third years, and the fourth and fifth years together. During each of these periods, and many others, the affiliated portfolio earns significantly lower returns than the unaffiliated portfolio. The differences are economically significant as well, on the order of 3-5% a year.

In addition to the event-study methodology, we plan on evaluating returns using a calendar-time approach. In particular, we are currently estimating and tabulating abnormal portfolio returns using a Fama-French three-factor model. While our results are still preliminary, they seem to support the market model event-time return results. We plan on including the Fama-French abnormal return results in a future draft.

IV.4. What drives the trading behavior of small investors?

The main alternative explanation for the undiscriminating reaction of small investors to recommendations of affiliated and unaffiliated analysts is informational constraints. Small investors may be able to understand the distortions arising from affiliation, but it may be to costly for them – different from large investors – to find out which analysts are affiliated to which specific firms. As a result they may decide to follow analyst recommendations regardless, since the probability of randomly hitting an unaffiliated recommendation is high enough.

Three types of empirical findings, however, cast doubt on that hypothesis. First, a rational model of informational constraints would predict that small investors reacted on average less to analyst recommendations than those agents who are able to distinguish between affiliated and unaffiliated analysts. Since small investors are not able to differentiate between more and less distorted investment advice, the expected return from following recommendations is lower for them, and they should discount *all* recommendations. Our normalized measure of abnormal trade imbalances suggests that the opposite is the case. Relatively speaking, small investors react more positively to positive recommendations than large investors (Table V, Regression 2).

In addition, if costs of information prevented small investors to sort out affiliated recommendations, they should compensate for the informational constraint by paying more attention to analysts whose brokerages simply do not have an affiliated corporate finance department or whose banks never do any underwriting at all. In fact, these firms tend to advertise their "independence" so that the information should be easily accessible. However, their trading behavior indicates the opposite. Of the 382 brokerage firms who issue recommendations for the firms in our sample, 105 (27%) do not have a single match to an SDC underwriter firm who was either the lead or co-underwriter on an equity issue for a US firm from 1987 on. These brokers issue about 5% of the recommendations in our sample. Small investors react significantly less to their recommendations than to the average (affiliated or non-affiliated) recommendation.

Finally, the change in behavior of small analysts after the scandals of 2001 and 2002 deserve mention. In August 2001, media coverage of analysts' conflicts of interest peaked and the first lawsuit by an investor claiming he lost money due to a biased analysts recommendation was settled. In May 2002, extensive changes in the regulation of investment banking organization and analyst affiliation disclosure were initialized, and it was the period of the initial settlement with Merrill Lynch). Taking these two dates as cutoff points and rerunning the regressions of abnormal trade balances, we find that small investors start reacting more strongly to analysts of "independent" brokerages. This suggests that small investors started understanding the implications of incentive conflicts only after they saw evidence on the resulting distortions. Once they saw evidence such as Merrill's Henry Blodget referring to stocks he touted as "crap" they were well able to react appropriately and avoid affiliated analysts. The mere knowledge of an incentive conflict, however, appears to be insufficient.

V. Firm response

In a world with rational firms, biased consumer behavior does not only affect the consumers' welfare, but the entire organization of the market. Firms have incentives to tailor their product and information provision to take advantage of consumers' systematic deviations from optimal decision-making. In the case of stock market recommendations, it is profitable for investment banks to unify brokerage and corporate finance under one roof since investors systematically neglect analyst distortions.

An interesting – theoretical and empirical – question is whether competition among analysts may remedy this informational distortion. Do analysts compete for clients by providing more accurate recommendations? Given that, almost always, the affiliated brokerages are covering the stock, increased competition implies an increased number of non-affiliated analysts. Since unaffiliated analysts tend to bias their recommendations less, one may expect that competition also moderate the distortion in affiliated recommendations.

As a first attempt to address this question empirically, we analyze the relationship between the number of analysts covering a stock and the recommendation bias of affiliated analysts. For each recommendation, we calculate the number of analysts who had made a recommendation on the same stock in the past x months, for x = 1, 2, 6 and 12. Panel A of Table VII presents the summary statistics for the one-month coverage. We then relate the number of analysts to analysts "deviation" from the average recommendation over the past months. Columns (1) and (3) of Panel B show that, as expected, affiliated recommendations tend to lie above the average recommendation. Increased coverage, however, does not mitigate the effect. As we can see from Columns (2) and (4), the opposite appears to be the case. Affiliated analysts tend to bias their recommendations more when more analysts are covering the stock. While the mechanism behind the correlation of higher coverage and more upward bias cannot deduced from this regression, the results are a first indication that competition may not remedy informational distortion among analysts.

VI. Conclusion

Analysts face incentives to positively bias the information they provide to investors. These incentives are reflected in the very low number of sell and strong sell recommendations issued by all analysts, in particular by affiliated analysts

We find that small investors do not adjust for the incentives of an analyst who faces an underwriting affiliation. While large investors do not place additional buy pressure on a stock following an affiliated buy or strong buy recommendation, small investors do. Large investors react more weakly to positive affiliated recommendations than to unaffiliated recommendations, while small traders do the opposite, reacting most strongly when the incentive to distort recommendations is the highest.

Return results show that following affiliated recommendations consistently earns lower returns than following unaffiliated recommendations, over many possible time horizons. Small traders make losses by naively following affiliated analyst recommendations. Finally, additional competition does not seem to solve the problem. Affiliated analysts issue even higher recommendations when they face more competition. It is possible that small traders simply cannot identify underwriting affiliation, or that it is too costly for them to research an analyst's background. In this case, investors should react more cautiously to recommendations in general, but instead our abnormal trade imbalance results suggest that small traders react more strongly than large traders. Alternatively, small traders could focus on analysts from non-underwriting firms. Instead, small traders react less to these analysts. Only after scandals highlighted the effects of affiliation incentives did small traders moderate their reaction to affiliated recommendations, and begin focusing on non-underwriting brokerages. And only at that time did affiliated analysts begin issuing sell and strong sell recommendations. Awareness of the incentives was not sufficient to modify behavior, but rather the investors needed be confronted with evidence on the resulting distortions. Our findings also have implications for the policy debate about the appropriate regulations to be imposed on brokerage houses. Our results suggest that simply informing agents of potential conflicts of interest may not be enough to remedy their behavior. Instead, public and direct "warning" about the recommendations of certain types of analysts appears to be necessary.

We intend to pursue this topic further in several ways. First, we have planned additional tests, including alternate tests for return differences and for investor reactions to competition. We also plan to analyze earnings forecasts, as another source of information from analysts to investors. Our results thus far indicate that analyst incentives affect their recommendations, with competition among analysts failing to mitigate the effect. Overall, the traditional economic assumption of uninformed agents taking into account the incentives of informed agents, does not seem to hold in the market for information about stocks.

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TABLE I
Sample of Recommendations

Panel A: Entire Sample	Sample size	Percentage within category					Numerical translation[1]	
		Strong sell	Sell	Hold	Buy	Strong buy	Mean	Standard deviation
All	121,130	1.72	2.86	36.84	32.90	25.67	3.78	0.92
Unaffiliated	110,113	1.82	2.95	37.75	32.27	25.22	3.76	0.92
Affiliated (to recommended firm)	8,466	0.73	1.61	25.68	39.56	32.42	4.01	0.84
IPO lead-underwriting (past 5 years)	1,104	0.63	1.45	23.82	38.41	35.69	4.07	0.84
SEO lead-underwriting (past 2 years)	1,198	0.42	1.50	21.87	39.90	36.31	4.10	0.82
Co-underwriting equity[2]	4,143	0.99	1.62	26.43	38.79	32.17	4.00	0.86
Future SEO (next year)	437	0.00	0.46	14.19	44.16	41.19	4.26	0.71
Future SEO (next 2 years)	228	0.00	0.00	14.47	48.25	37.28	4.23	0.68
Bond lead underwriting (past one year)	2,083	0.62	1.87	27.99	39.85	29.67	3.96	0.84
Never Affiliated (to any firm)[3]	6,418	3.91	4.25	36.63	28.01	27.19	3.70	1.04

Panel B: Subsample of firms with an IPO in the past 5 years or SEO in the past 2 years or bond in the past year	Sample size	Percentage within category					Numerical translation[1]	
		Strong sell	Sell	Hold	Buy	Strong buy	Mean	Standard deviation
All	54,952	1.55	2.47	34.99	33.73	27.24	3.83	0.91
Unaffiliated	45,523	1.71	2.59	36.7	32.58	26.42	3.79	0.92
Affiliated	8,237	0.75	1.65	25.88	39.43	32.28	4.01	0.85

[1] The numercial translation uses the scheme 1=strong sell, 2=sell, 3=hold, 4=buy, 5=strong buy.

[2] We exclude co-underwriters who are also lead underwriters (on another issuance) to avoid double-counting.

[3] A brokerage firm is "Never Affiliated" if it does not have any (lead or co-underwriter) equity or bond underwriting affiliation during the entire sample period.

TABLE II.
Industry Summary Statistics

North American Industry Codes of recommended firms, split up by affiliation. Entire sample period 10/29/1993-12/31/2002

Industry (NAIC)	Subsample of Recommendations: All	IPO affiliation	SEO affiliation	Co-affiliation	Any equity affiliation	No affiliation	Never affiliated	%-point diff. "any affiliation minus no affiliation"
All	233,698	2,016	2,334	7,524	11,874	222,170	12,442	
Agriculture	514	0	14	10	24	490	26	
	0.22%	0.00%	0.60%	0.13%	0.20%	0.22%	0.21%	-0.02%
Mining	15,233	124	192	436	752	14,509	830	
	6.52%	6.15%	8.23%	5.79%	6.33%	6.53%	6.67%	-0.20%
Utilities	12,446	28	202	484	714	11,734	532	
	5.33%	1.39%	8.65%	6.43%	6.01%	5.28%	4.28%	0.73%
Construction	2,910	8	30	86	124	2,786	96	
	1.25%	0.40%	1.29%	1.14%	1.04%	1.25%	0.77%	-0.21%
Manufacturing	93,768	710	832	2,614	4,156	89,710	5,336	
	40.12%	35.22%	35.65%	34.74%	35.00%	40.38%	42.89%	-5.38%
Wholesale Trade	8,350	96	108	324	528	7,834	476	
	3.57%	4.76%	4.63%	4.31%	4.45%	3.53%	3.83%	0.92%
Retail Trade	19,572	206	168	584	958	18,664	836	
	8.37%	10.22%	7.20%	7.76%	8.07%	8.40%	6.72%	-0.33%
Transportation and Warehousing	5,980	46	72	222	340	5,660	210	
	2.56%	2.28%	3.08%	2.95%	2.86%	2.55%	1.69%	0.32%
Information	15,660	160	140	540	840	14,846	966	
	6.70%	7.94%	6.00%	7.18%	7.07%	6.68%	7.76%	0.39%
Finance and Insurance	36,010	344	306	1,250	1,900	34,154	2,014	
	15.41%	17.06%	13.11%	16.61%	16.00%	15.37%	16.19%	0.63%
Real Estate and Rental Leasing	2,128	88	58	208	354	1,796	108	
	0.91%	4.37%	2.49%	2.76%	2.98%	0.81%	0.87%	2.17%
Professional, Scientific, Technical	5,361	48	56	158	262	5,107	306	
	2.29%	2.38%	2.40%	2.10%	2.21%	2.30%	2.46%	-0.09%
Mgmt of Companies and Enterpris	0	0	0	0	0	0	0	
	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Administrative and Support and W	3,380	56	34	140	230	3,156	200	
	1.45%	2.78%	1.46%	1.86%	1.94%	1.42%	1.61%	0.52%
Educational Services	510	6	10	18	34	476	76	
	0.22%	0.30%	0.43%	0.24%	0.29%	0.21%	0.61%	0.07%
Health Care and Social Assistanc	4,232	10	46	214	270	3,962	184	
	1.81%	0.50%	1.97%	2.84%	2.27%	1.78%	1.48%	0.49%
Arts, Entertainment, Recreation	886	22	14	70	106	780	14	
	0.38%	1.09%	0.60%	0.93%	0.89%	0.35%	0.11%	0.54%
Accommodation and Food service	5,914	24	30	86	140	5,786	196	
	2.53%	1.19%	1.29%	1.14%	1.18%	2.60%	1.58%	-1.43%
Other Services	386	22	22	36	80	324	22	
	0.17%	1.09%	0.94%	0.48%	0.67%	0.15%	0.18%	0.53%
Public Administration	0	0	0	0	0	0	0	
	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%

TABLE III.
Persistence of Recommendations

A. Sample Statistics

	Mean (Median) number of days until new recommendation (same stock, same analyst)					
	Overall	Strong sell	Sell	Hold	Buy	Strong buy
Unaffiliated	307.89	186.15	181.37	323.35	292.69	331.88
	(181)	(098)	(103.0)	(180)	(176)	(207)
Affiliated (IPO, SEO, co-underwriters)	357.23	103.18	90.92	296.05	360.67	403.27
	(228)	(57)	(59)	(182.0)	(230)	(272.0)

	Mean (Median) number of days until new recommendation (same stock, same analyst)	
	before upgrade	before downgrade
Unaffiliated	297.18	316.79
	(162)	(193.0)
Affiliated (IPO, SEO, co-underwriters)	301.63	390.78
	(178)	(259)

B. Regression (controlling for recommendation type)

	Days until new recommendation (same stock, same analyst)					
		(SE)	(t-stat)		(SE)	(t-stat)
"Strong Sell, Sell, or Hold" (dummy)	292.118	(2.227)	131.15	292.125	(2.227)	131.20
"Buy" (dummy)	270.876	(2.301)	117.74	271.059	(2.299)	117.90
"Strong Buy" (dummy)	308.161	(2.620)	117.61	308.203	(2.618)	117.71
(Strong Sell, Sell, Hold)* (Any Affiliation)	-33.890	(12.323)	-2.75			
(Strong Sell, Sell, Hold)* (IPO Affiliation)				-17.550	(31.372)	-0.56
(Strong Sell, Sell, Hold)* (SEO Affiliation)				-6.715	(29.831)	-0.23
(Strong Sell, Sell, Hold)* (Co-Affiliation)				-43.276	(14.656)	-2.95
(Buy)* (Any Affiliation)	50.397	(9.374)	5.38			
(Buy)* (IPO Affiliation)				26.083	(22.061)	1.18
(Buy)* (SEO Affiliation)				89.620	(21.636)	4.14
(Buy)* (Co-Affiliation)				39.540	(11.340)	3.49
(Strong Buy)* (Any Affiliation)	33.671	(10.346)	3.25			
(Strong Buy)* (IPO Affiliation)				65.820	(23.036)	2.86
(Strong Buy)* (SEO Affiliation)				49.052	(24.389)	2.01
(Strong Buy)* (Co-Affiliation)				17.644	(12.604)	1.40

TABLE IV.

Comparison to "Consensus" of Recommendations

	Difference to "Consensus" (1 month)			
		(SE)		(SE)
"Strong Sell, Sell, or Hold" (dummy)	-0.787	(0.004)	-0.787	(0.004)
"Buy" (dummy)	0.143	(0.005)	0.143	(0.005)
"Strong Buy" (dummy)	1.074	(0.006)	1.074	(0.006)
(Strong Sell, Sell, Hold)* (Any Affiliation)	0.094	(0.026)		
(Strong Sell, Sell, Hold)* (IPO Affiliation)			0.037	(0.070)
(Strong Sell, Sell, Hold)* (SEO Affiliation)			0.195	(0.063)
(Strong Sell, Sell, Hold)* (Co-Affiliation)			0.077	(0.031)
(Buy)* (Any Affiliation)	-0.154	(0.023)		
(Buy)* (IPO Affiliation)			-0.153	(0.060)
(Buy)* (SEO Affiliation)			-0.089	(0.050)
(Buy)* (Co-Affiliation)			-0.167	(0.027)
(Strong Buy)* (Any Affiliation)	-0.180	(0.024)		
(Strong Buy)* (IPO Affiliation)			-0.169	(0.062)
(Strong Buy)* (SEO Affiliation)			-0.183	(0.051)
(Strong Buy)* (Co-Affiliation)			-0.167	(0.030)

TABLE V.

Trade Reaction

Panel A. Summary Statistics Daily Trading for Sample Firms

	Mean	Median	Std. Dev.	Min	Max
Number of small buy-initiated trades	29.97	13	50.98	0	1,702
Number of large buy-initiated trades	21.49	3	62.14	0	1,911
Number of small sell-initiated trades	26.79	13	42.76	0	2,453
Number of large sell-initiated trades	18.06	3	51.09	0	1,563
total small trades	56.76	26	91.06	0	3,506
total large trades	39.55	6	112.42	0	3,339
Δ(buy-sell) initiated small trades	3.18	0	23.71	-1,440	965
Δ(buy-sell) initiated large trades	3.43	0	17.44	-660	791
Dollar value small buy-initiated trades	255,760	99,175	461,493	0	12,300,000
Dollar value large buy-initiated trades	5,579,860	417,750	22,700,000	0	4,860,000,000
Dollar value small sell-initiated trades	228,392	98,550	387,906	0	16,000,000
Dollar value large sell-initiated trades	4,666,593	382,524	18,300,000	0	3,120,000,000
Dollar value total small trades	484,153	204,600	828,517	0	22,700,000
Dollar value total large trades	10,200,000	918,875	40,000,000	0	5,510,000,000
Dollar value of (buy-sell) small trades	27,368	2,338	201,131	-10,600,000	8,854,894
Dollar value of (buy-sell) large trades	913,267	0	9,824,109	-1,430,000,000	4,860,000,000
N	*2,996,265*				

Panel B. Summary Statistics Trade Imbalance - Sum over Event Days 0 and 1

	Mean	Median	Std. Dev.	Min	Max
Δ(buy-sell) initiated small trades	9.65	3	42.94	-1,145	663
Δ(buy-sell) initiated large trades	9.97	2	33.65	-449	588
Dollar value of (buy-sell) small trades	81,454	20,963	372,201	-7,753,500	5,752,538
Dollar value of (buy-sell) large trades	2,462,167	149,125	24,800,000	-1,200,000,000	1,570,000,000
Normalized Imbalance of small trades	0.1087	0.1265	1.6348	-15.8431	7.1467
Normalized Imbalance of large trades	-0.0063	0.0141	1.4083	-9.4254	7.1931
N	*86,962*				

Panel C. Regression of Net Trades, Buy-Sell Initiated, Sum Over Event Days 0 and 1

Difference in Number of Buy and Sell Initiated Trade

	Coef.	Std. Err.	t-stat
Strong Sell	14.147	1.875	7.54
Sell	10.444	1.600	6.53
Hold	15.642	0.395	39.64
Buy	20.874	0.406	51.39
Strong Buy	24.091	0.462	52.16
(Strong Sell)*Affiliation	-14.184	13.219	-1.07
(Sell)*Affiliation	-3.838	11.944	-0.32
(Hold)*Affiliation	-9.361	2.174	-4.31
(Buy)*Affiliation	-13.673	1.649	-8.29
(Strong Buy)*Affiliation	-13.399	1.764	-7.60
(Strong Sell)*(Small Trade)	-5.746	2.652	-2.17
(Sell)*(Small Trade)	-1.798	2.263	-0.79
(Hold)*(Small Trade)	1.373	0.558	2.46
(Buy)*(Small Trade)	-0.497	0.574	-0.87
(Strong Buy)*(Small Trade)	-0.545	0.653	-0.83
(Strong Sell)*(Affiliation)*(Small Trade)	-8.624	18.695	-0.46
(Sell)*(Affiliation)*(Small Trade)	7.253	16.891	0.43
(Hold)*(Affiliation)*(Small Trade)	2.722	3.074	0.89
(Buy)*(Affiliation)*(Small Trade)	8.241	2.333	3.53
(Strong Buy)*(Affiliation)*(Small Trade)	5.095	2.494	2.04

Sample size: 173,968. R-squared: 0.0761.

Panel D. Regression of Normalized Trade Imbalance, Sum Over Event Days 0 and 1

Sum of Normalized Trade Imbalance Over Event Perio(			
	Coef.	Std. Err.	t-stat
Strong Sell	-0.103	0.042	-2.46
Sell	-0.118	0.036	-3.29
Hold	-0.091	0.009	-10.33
Buy	0.011	0.009	1.22
Strong Buy	0.112	0.010	10.86
(Strong Sell)*Affiliation	-0.195	0.296	-0.66
(Sell)*Affiliation	0.094	0.268	0.35
(Hold)*Affiliation	-0.001	0.049	-0.02
(Buy)*Affiliation	-0.068	0.037	-1.84
(Strong Buy)*Affiliation	-0.129	0.040	-3.26
(Strong Sell)*(Small Trade)	-0.002	0.059	-0.04
(Sell)*(Small Trade)	-0.021	0.051	-0.42
(Hold)*(Small Trade)	0.098	0.013	7.88
(Buy)*(Small Trade)	0.123	0.013	9.59
(Strong Buy)*(Small Trade)	0.131	0.015	8.94
(Strong Sell)*(Affiliation)*(Small Trade)	-0.642	0.419	-1.53
(Sell)*(Affiliation)*(Small Trade)	-0.180	0.378	-0.48
(Hold)*(Affiliation)*(Small Trade)	0.006	0.069	0.09
(Buy)*(Affiliation)*(Small Trade)	0.081	0.052	1.55
(Strong Buy)*(Affiliation)*(Small Trade)	0.106	0.056	1.89

Sample size: 173,924. R-squared: 0.0063.

TABLE VI.

Correlations of Institutional Ownership Change[1] to Trading Variables

(P-values in parentheses.)

	Small Investors Values	Large Investors Values
Sum of daily abnormal trade imbalances over last quarter	-0.073 (0.000)	0.070 (0.000)
Quarterly trade imbalance	-0.082 (0.000)	0.088 (0.000)
Quarterly trade imbalance, number of shares	-0.089 (0.000)	0.122 (0.000)
Quarterly trade imbalance, dollar value	-0.085 (0.000)	0.119 (0.000)

[1] Ownership Change is measured as the change in the percentage of shares outstanding owned by institutions filing a 13F

TABLE VII.
Portfolio Returns

		Abnormal returns of portfolios based on recommendations						affiliated abnormal portfolio returns		
		Affiliated Analysts			Unaffiliated Analysts					
	Period		SE	t-stat.		SE	t-stat.		SE	t-stat.
MM, E	(-10,-2)	-0.67%	-0.12%	5.581	-0.09%	-0.04%	2.052	0.58%	0.13%	4.538
	(-1,+1)	0.51%	0.07%	7.417	0.70%	0.03%	26.768	0.19%	0.07%	2.583
	(+2,+64)	-1.89%	-0.32%	5.980	-0.96%	-0.12%	8.019	0.93%	0.34%	2.752
	(+2,+128)	-4.53%	-0.45%	10.087	-3.10%	-0.17%	18.349	1.43%	0.48%	2.980
	(+2,+255)	-11.36%	-0.63%	17.899	-7.85%	-0.24%	32.831	3.51%	0.68%	5.175
	(+256,+510)	-12.38%	-0.64%	19.472	-7.09%	-0.24%	29.587	5.29%	0.68%	7.786
	(+511,+765)	-10.52%	-0.64%	16.545	-6.14%	-0.24%	25.606	4.38%	0.68%	6.445
	(+766,+1275)	-31.00%	-0.90%	34.475	-21.55%	-0.34%	63.593	9.45%	0.96%	9.834
MM, V	(-10,-2)	-0.59%	-0.12%	5.047	-0.02%	-0.04%	0.461	0.57%	0.12%	4.571
	(-1,+1)	0.47%	0.07%	6.940	0.69%	0.03%	26.733	0.22%	0.07%	3.036
	(+2,+64)	-1.67%	-0.31%	5.389	-0.80%	-0.12%	6.715	0.87%	0.33%	2.620
	(+2,+128)	-3.58%	-0.44%	8.147	-2.23%	-0.17%	13.196	1.35%	0.47%	2.867
	(+2,+255)	-7.71%	-0.62%	12.404	-4.82%	-0.24%	20.207	2.89%	0.67%	4.341
	(+256,+510)	-8.58%	-0.62%	13.785	-3.84%	-0.24%	16.042	4.74%	0.67%	7.108
	(+511,+765)	-5.03%	-0.62%	8.083	-2.17%	-0.24%	9.078	2.86%	0.67%	4.290
	(+766,+1275)	-7.79%	-0.88%	8.853	-4.01%	-0.34%	11.848	3.78%	0.94%	4.009

MM indicates market model (beta correction)

E indicates equal weighted market index

V indicates value weighted market index

Returns based on recommendations made between February 1994 and July 2001, inclusive.

This table presents buy-and-hold returns. Results for cumulative abnormal returns are similar.

TABLE VIII.

The Effect of Coverage on Recommendation Bias

A. Summary Statistics

	Mean	Median	25%	75%	Standard Deviation
"Consensus" [1]	3.84	3.87	3.50	4.17	0.51
Difference Recommendation to "Consensus"	-0.06	0.00	-0.75	0.67	0.95
Coverage (# Analysts[2])	1.5	1.00	0.00	2.00	1.85

B. Regression of Deviation from "Consensus"

Affiliation	0.1312	0.0662		
	(0.0162; 8.09)	(0.0273; 2.43)		
IPO Affiliation			0.0981	0.0196
			(0.417; 2.35)	(0.0700; 0.28)
SEO Affiliation			0.2339	0.1309
			(0.0383; 6.10)	(0.0631; 2.07)
Co-underwriter Affiliation			0.1038	0.0532
			(0.0192; 5.40)	(0.0326; 1.63)
Never Affiliated	-0.1565	-0.1384	-0.1565	-0.1385
	(0.0153; -10.22)	(0.0252; -5.49)	(0.0153; -10.23)	(0.0252; -5.49)
Analysts (#)	-0.0008	-0.0014	-0.0008	-0.0014
	(0.0019; -0.44)	(0.0019; -0.71)	(0.0019; -0.44)	(0.0019; -0.72)
Analysts (#)*Affiliation		0.0349		
		(-0.0117; 2.97)		
(Analysts #)*IPO Affiliation				0.0464
				(0.0323; 1.44)
(Analysts #)*SEO Affiliation				0.0554
				(0.0554; 2.06)
(Analysts #)*Co-underwriter Affiliation				0.0268
				(0.0140; 1.92)
(Analysts #)*(Never Affiliated)		0.0128		-0.0086
		(-0.0086; -1.49)		(0.0095; -0.91)
Constant	-0.0131	-0.0131	-0.0130	-0.0118
	(0.0055; -2.40)	(0.0052; -2.51)	(0.0054; -2.38)	(0.0056; -2.11)

Number of observations 122,730.

Sample period: 1993-2000 (Regulation FD effective on Oct. 23, 2000).

[1] Average of analyst recommendations over the last month.

[2] Analysts (#) is the number of analysts who have issued a recommendation for the specific stock during the last month.